Conventions, Accuracy Metrics, Classification, Regression

Nipun Batra

IIT Gandhinagar

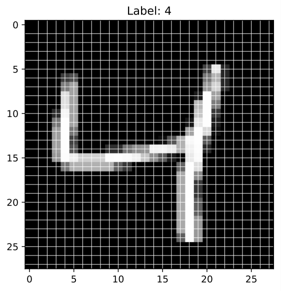
July 30, 2025

Outline

Digit Recognition Problem

Let us work on the digit recognition problem.

Notebook: rule-based-vs-ml.html



Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

- The heights of each of the | need to be similar within tolerance

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

- The heights of each of the | need to be similar within tolerance

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

- The heights of each of the | need to be similar within tolerance
- Each of the | can be slightly slanted. Similarly the horizontal line can be slanted.

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

- The heights of each of the | need to be similar within tolerance
- Each of the | can be slightly slanted. Similarly the horizontal line can be slanted.

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

- The heights of each of the | need to be similar within tolerance
- Each of the | can be slightly slanted. Similarly the horizontal line can be slanted.
- There can be some cases of 4 where the first | is at 45 degrees

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

- The heights of each of the | need to be similar within tolerance
- Each of the | can be slightly slanted. Similarly the horizontal line can be slanted.
- There can be some cases of 4 where the first | is at 45 degrees

Rule-based Approach for Digit Recognition

Maybe 4 can be thought of as: | + — + | + another vertical |

- The heights of each of the | need to be similar within tolerance
- Each of the | can be slightly slanted. Similarly the horizontal line can be slanted.
- There can be some cases of 4 where the first | is at 45 degrees
- There can be some cases of 4 where the width of each stroke is different

Pop Quiz: Rule-Based vs ML

Quick Quiz 1

Why is it difficult to write rules for digit recognition?

a) Digits are always the same

Answer: b) Handwriting variations make rule-based approaches extremely complex!

Pop Quiz: Rule-Based vs ML

Quick Quiz 1

Why is it difficult to write rules for digit recognition?

a) Digits are always the same
b) Variations in handwriting, rotation, thickness make rules complex

Answer: b) Handwriting variations make rule-based approaches extremely complex!

Pop Quiz: Rule-Based vs ML

Quick Quiz 1

Why is it difficult to write rules for digit recognition?

a) Digits are always the same
b) Variations in handwriting, rotation, thickness make rules complex
c) Rules are faster than ML

Answer: b) Handwriting variations make rule-based approaches extremely complex!

Apple Quality Features

- Size

Apple Quality Features

- Size

Apple Quality Features

- Size

Apple Quality Features

- Size
- Colour

Apple Quality Features

- Size
- Colour

Apple Quality Features

- Size
- Colour
- Texture

Should We Include Sample Numbers?

Answer: Usually no! Sample numbers are typically arbitrary identifiers and not meaningful features. Let us remove it.

Should We Include Sample Numbers?

Answer: Usually no! Sample numbers are typically arbitrary identifiers and not meaningful features. Let us remove it.
Let us modify our data table for now.

Colour	**Size**	**Texture**	**Condition**
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad

Training Set Components

The training set consists of two parts:

Training Set Components

The training set consists of two parts:

Training Set Components

The training set consists of two parts:

1. Features (Input Variables)

Training Set Components

The training set consists of two parts:

1. Features (Input Variables)

Training Set Components

The training set consists of two parts:

1. Features (Input Variables)
2. Output or Response Variable

Dataset Notation

We call this matrix as $\mathcal{D}$, containing:

1. Feature matrix ($\mathbf{X} \in \mathbb{R}^{n \times d}$) containing data of n samples each of which is d dimensional.

Dataset Notation

We call this matrix as $\mathcal{D}$, containing:

1. Feature matrix ($\mathbf{X} \in \mathbb{R}^{n \times d}$) containing data of n samples each of which is d dimensional.
2. Output vector ($\mathbf{y} \in \mathbb{R}^{n}$) containing output variable for n samples.

Dataset Example

Example (after encoding): $\mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$ (Orange=1, Small=0, Smooth=1)

Dataset Example

Example (after encoding): $\mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$ (Orange=1, Small=0, Smooth=1)

Dataset Example

Example (after encoding): $\mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$ (Orange=1, Small=0, Smooth=1)

- Complete dataset: $\mathcal{D} = \{(\mathbf{x}_i^\top, y_i)\}_{i=1}^n$

Machine Learning Goal

Learn f: Condition $= f($colour, size, texture$)$

Machine Learning Goal

Learn f: Condition $= f($colour, size, texture$)$

Machine Learning Goal

Learn f: Condition $= f($colour, size, texture$)$

1. From Training Dataset

Machine Learning Goal

Learn f: Condition $= f($colour, size, texture$)$

1. From Training Dataset

Machine Learning Goal

Learn f: Condition $= f($colour, size, texture$)$

1. From Training Dataset
2. To Predict the condition for the Testing set

Colour	**Size**	**Texture**	**Condition**
Orange	Small	Smooth	Good
Red	Small	Rough	Good
Orange	Medium	Smooth	Bad
Yellow	Large	Smooth	Bad
Red	Large	Rough	?
Orange	Large	Rough	?

Can We Judge Performance Only on Test Set?

A: Ideally, no!

Can We Judge Performance Only on Test Set?

A: Ideally, no!

Can We Judge Performance Only on Test Set?

A: Ideally, no!

- Ideally - we want to predict “well” on all possible inputs. But, can we test that?

Can We Judge Performance Only on Test Set?

A: Ideally, no!

- Ideally - we want to predict "well" on all possible inputs. But, can we test that?

Can We Judge Performance Only on Test Set?

A: Ideally, no!

- Ideally - we want to predict “well” on all possible inputs. But, can we test that?
- No! Since, the test set is only a sample from all possible inputs.

Training vs Test Sets

Both the training set and the test set are samples drawn from the hidden true distribution (also sometimes called population)

Training vs Test Sets

Both the training set and the test set are samples drawn from the hidden true distribution (also sometimes called population)

More discussion later once we study bias and variance

Energy Consumption Example

- # People (More people $\implies$ More Energy)

Energy Consumption Example

- # People (More people $\implies$ More Energy)

Energy Consumption Example

- # People (More people $\implies$ More Energy)

Energy Consumption Example

- # People (More people $\implies$ More Energy)
- Temperature (Higher Temp. $\implies$ Higher Energy)

Energy Consumption Example

- # People (More people $\implies$ More Energy)
- Temperature (Higher Temp. $\implies$ Higher Energy)

# People	Temp (C)	Energy (kWh)
4000	30	30
4200	30	32
4200	35	40
3000	20	?
1000	45	?

Pop Quiz: Training Data

Quick Quiz 2

What makes a good feature for machine learning?

a) Sample ID numbers

Answer: b) Features should be meaningful and related to what you're predicting!

Pop Quiz: Training Data

Quick Quiz 2

What makes a good feature for machine learning?

a) Sample ID numbers
b) Meaningful characteristics that relate to the output

Answer: b) Features should be meaningful and related to what you're predicting!

Pop Quiz: Training Data

Quick Quiz 2

What makes a good feature for machine learning?

a) Sample ID numbers
b) Meaningful characteristics that relate to the output
c) Random numbers

Answer: b) Features should be meaningful and related to what you're predicting!

Classification vs Regression

- Classification

Classification vs Regression

- Classification

Classification vs Regression

- Classification

Classification vs Regression

- Classification
  - Output variable is discrete

Classification vs Regression

- Classification
  - Output variable is discrete

Classification vs Regression

- Classification
    - Output variable is discrete
    - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous
  - i.e. $y_i \in \mathbb{R}$

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous
  - i.e. $y_i \in \mathbb{R}$

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous
  - i.e. $y_i \in \mathbb{R}$
  - Examples - Predicting:

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous
  - i.e. $y_i \in \mathbb{R}$
  - Examples - Predicting:

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \dots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous
  - i.e. $y_i \in \mathbb{R}$
  - Examples - Predicting:
    - How much energy will campus consume?

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \dots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous
  - i.e. $y_i \in \mathbb{R}$
  - Examples - Predicting:
    - How much energy will campus consume?

Classification vs Regression

- Classification
  - Output variable is discrete
  - i.e. $y_i \in \{1, 2, \ldots, k\}$ where k is number of classes
  - Examples - Predicting:
    - Will I get a loan? (Yes, No)
    - What is the quality of fruit? (Good, Bad)
- Regression
  - Output variable is continuous
  - i.e. $y_i \in \mathbb{R}$
  - Examples - Predicting:
    - How much energy will campus consume?
    - How much rainfall will fall?

Pop Quiz: Problem Types

Quick Quiz 3

Predicting house prices is an example of:

a) Classification (discrete output)

Answer: b) Regression - house prices are continuous values!

Pop Quiz: Problem Types

Quick Quiz 3

Predicting house prices is an example of:

a) Classification (discrete output)
b) Regression (continuous output)

Answer: b) Regression - house prices are continuous values!

Pop Quiz: Problem Types

Quick Quiz 3

Predicting house prices is an example of:

a) Classification (discrete output)
b) Regression (continuous output)
c) Neither

Answer: b) Regression - house prices are continuous values!

Accuracy Calculation

$$\text{Accuracy} = \frac{|\{i : y_i = \hat{y}_i\}|}{n} = \frac{3}{5} = 0.6$$

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$
  - Reads as: "Number of indices i such that $y_i = \hat{y}_i$"

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$
  - Reads as: "Number of indices i such that $y_i = \hat{y}_i$"
  - Counts how many samples satisfy the condition

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$
  - Reads as: "Number of indices i such that $y_i = \hat{y}_i$"
  - Counts how many samples satisfy the condition

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$
  - Reads as: "Number of indices i such that $y_i = \hat{y}_i$"
  - Counts how many samples satisfy the condition

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$
  - Reads as: "Number of indices i such that $y_i = \hat{y}_i$"
  - Counts how many samples satisfy the condition
- **Alternative: Indicator function notation**

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} \mathbf{1}[y_i = \hat{y}_i]}{n}$$

$$\text{where } \mathbf{1}[\text{condition}] = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{if condition is false} \end{cases}$$

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$
  - Reads as: "Number of indices i such that $y_i = \hat{y}_i$"
  - Counts how many samples satisfy the condition
- **Alternative: Indicator function notation**

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} \mathbf{1}[y_i = \hat{y}_i]}{n}$$

$$\text{where } \mathbf{1}[\text{condition}] = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{if condition is false} \end{cases}$$

Accuracy Notation

- **Set cardinality notation:** $|\{i : y_i = \hat{y}_i\}|$
  - Reads as: "Number of indices i such that $y_i = \hat{y}_i$"
  - Counts how many samples satisfy the condition
- **Alternative: Indicator function notation**

$$\text{Accuracy} = \frac{\sum_{i=1}^{n} \mathbf{1}[y_i = \hat{y}_i]}{n}$$

$$\text{where } \mathbf{1}[\text{condition}] = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{if condition is false} \end{cases}$$

- Both notations are mathematically equivalent and commonly used in ML literature

When Precision/Recall Matter

Cases for this:

- Cancer Screening

When Precision/Recall Matter

Cases for this:

- Cancer Screening
- Planet Detection

Precision Metric

$$\text{Precision} = \frac{|\{i : y_i = \hat{y}_i = \text{Good}\}|}{|\{i : \hat{y}_i = \text{Good}\}|} = \frac{2}{4} = 0.5$$

Definition: "The fraction of relevant instances among the retrieved instances"
In simple terms: Out of all times we predict "Good", how many times is it actually "Good"?

Accuracy vs Precision/Recall

$$\text{Accuracy} = \frac{98}{100} = 0.98$$
$$\text{Recall} = \frac{0}{1} = 0$$
$$\text{Precision} = \frac{0}{1} = 0$$

Confusion Matrix

		Ground Truth	
		Positive	Negative
Predicted	Positive	**True Positive (TP)**	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

Confusion Matrix

		Ground Truth	
		Positive	Negative
Predicted	Positive	**True Positive (TP)**	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

Key Insight

Each cell represents a different type of prediction outcome:

Confusion Matrix

		Ground Truth	
		Positive	Negative
Predicted	Positive	**True Positive (TP)**	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

Key Insight

Each cell represents a different type of prediction outcome:

- TP: Correctly predicted positive

Confusion Matrix

		Ground Truth	
		Positive	Negative
Predicted	Positive	**True Positive (TP)**	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

Key Insight

Each cell represents a different type of prediction outcome:

- TP: Correctly predicted positive
- FP: Incorrectly predicted positive

Confusion Matrix

		Ground Truth	
		Positive	Negative
Predicted	Positive	**True Positive (TP)**	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

Key Insight

Each cell represents a different type of prediction outcome:

- TP: Correctly predicted positive
- FP: Incorrectly predicted positive
- FN: Missed a positive (dangerous!)

Confusion Matrix

		Ground Truth	
		Positive	Negative
Predicted	Positive	**True Positive (TP)**	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

Key Insight

Each cell represents a different type of prediction outcome:

- TP : Correctly predicted positive
- FP : Incorrectly predicted positive
- FN : Missed a positive (dangerous!)
- TN : Correctly predicted negative

Precision: "How accurate are my positive predictions?"

		Ground Truth	
		Positive	Negative
Predicted	Positive	**TP**	**FP**
	Negative	FN	TN

$$\text{Precision} = \frac{\boxed{TP}}{\boxed{TP} + \boxed{FP}} = \frac{\text{Correct Positives}}{\text{All Predicted Positives}}$$

Precision: "How accurate are my positive predictions?"

		Ground Truth	
		Positive	Negative
Predicted	Positive	**TP**	**FP**
	Negative	FN	TN

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} = \frac{\text{Correct Positives}}{\text{All Predicted Positives}}$$

Focus: Look at the PREDICTED POSITIVE ROW

Question: When I predict "positive", how often am I right?
Answer: Out of all my positive predictions (TP + FP), TP are correct.

Recall: "How many actual positives did I find?"

		Ground Truth	
		Positive	Negative
Predicted	Positive	**TP**	FP
	Negative	**FN**	TN

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{Correct Positives}}{\text{All Actual Positives}}$$

Recall: "How many actual positives did I find?"

		Ground Truth	
		Positive	Negative
Predicted	Positive	**TP**	FP
	Negative	**FN**	TN

$$\text{Recall} = \frac{TP}{TP + FN} = \frac{\text{Correct Positives}}{\text{All Actual Positives}}$$

Focus: Look at the ACTUAL POSITIVE COLUMN

Question: Of all things that ARE positive, how many did I catch?
Answer: Out of all actual positives (TP + FN), I found TP of them.

Example: Medical Diagnosis

Let's say we're testing for a disease:

Test Says		Actually Has Disease	
		Yes	No
	Positive	**90**	**10**
	Negative	**5**	**895**

Example: Medical Diagnosis

Let's say we're testing for a disease:

		Actually Has Disease	
		Yes	No
Test Says	Positive	**90**	**10**
	Negative	**5**	**895**

$$\text{Precision} = \frac{90}{90 + 10} = \frac{90}{100} = 0.90 \text{ (90\%)}$$

$$\text{Recall} = \frac{90}{90 + 5} = \frac{90}{95} = 0.95 \text{ (95\%)}$$

$$\text{Accuracy} = \frac{90 + 895}{1000} = 0.985 \text{ (98.5\%)}$$

Example: Medical Diagnosis

Let's say we're testing for a disease:

		Actually Has Disease	
		Yes	No
Test Says	Positive	**90**	**10**
	Negative	**5**	**895**

$$\text{Precision} = \frac{\boxed{90}}{\boxed{90} + \boxed{10}} = \frac{90}{100} = 0.90 \text{ (90\%)}$$

$$\text{Accuracy} = \frac{\boxed{90} + \boxed{895}}{1000} = 0.985 \text{ (98.5\%)}$$

Example: Medical Diagnosis

Let's say we're testing for a disease:

		Actually Has Disease	
		Yes	No
Test Says	Positive	**90**	**10**
	Negative	**5**	**895**

$$\text{Precision} = \frac{\boxed{90}}{\boxed{90} + \boxed{10}} = \frac{90}{100} = 0.90 \text{ (90\%)}$$

$$\text{Recall} = \frac{\boxed{90}}{\boxed{90} + \boxed{5}} = \frac{90}{95} = 0.95 \text{ (95\%)}$$

$$\text{Accuracy} = \frac{\boxed{90} + \boxed{895}}{1000} = 0.985 \text{ (98.5\%)}$$

Mean Error Issues

Is there any downside with using mean error?

Mean Error Issues

Is there any downside with using mean error? Errors can get cancelled out

Pop Quiz: Metrics Choice

Quick Quiz 4

For cancer detection (1 positive case in 1000), which metric is most important?

a) Accuracy only

Answer: b) Recall - we cannot afford to miss cancer cases!

Pop Quiz: Metrics Choice

Quick Quiz 4

For cancer detection (1 positive case in 1000), which metric is most important?

a) Accuracy only
b) Recall (finding all cancer cases)

Answer: b) Recall - we cannot afford to miss cancer cases!

Pop Quiz: Metrics Choice

Quick Quiz 4

For cancer detection (1 positive case in 1000), which metric is most important?

a) Accuracy only
b) Recall (finding all cancer cases)
c) Speed of prediction

Answer: b) Recall - we cannot afford to miss cancer cases!

Pop Quiz

Quick Quiz 1

Which metrics should you use for imbalanced datasets?

1. Accuracy only

Answer: c) Precision, recall, and F1-score give a more complete picture!

Pop Quiz

Quick Quiz 1

Which metrics should you use for imbalanced datasets?

1. Accuracy only
2. Mean squared error

Answer: c) Precision, recall, and F1-score give a more complete picture!

Pop Quiz

Quick Quiz 1

Which metrics should you use for imbalanced datasets?

1. Accuracy only
2. Mean squared error
3. Precision, recall, and F1-score

Answer: c) Precision, recall, and F1-score give a more complete picture!

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers
- **Classification vs Regression:**
  Discrete outputs vs continuous outputs

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers
- **Classification vs Regression:**
  Discrete outputs vs continuous outputs

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers
- **Classification vs Regression:**
  Discrete outputs vs continuous outputs
- **Accuracy isn't everything:**
  For imbalanced data, use precision, recall, F1-score

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers
- **Classification vs Regression:**
  Discrete outputs vs continuous outputs
- **Accuracy isn't everything:**
  For imbalanced data, use precision, recall, F1-score

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers
- **Classification vs Regression:**
  Discrete outputs vs continuous outputs
- **Accuracy isn't everything:**
  For imbalanced data, use precision, recall, F1-score
- **Visualization is crucial:**
  Always plot your data first

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers
- **Classification vs Regression:**
  Discrete outputs vs continuous outputs
- **Accuracy isn't everything:**
  For imbalanced data, use precision, recall, F1-score
- **Visualization is crucial:**
  Always plot your data first

Key Takeaways

- **ML vs Traditional Programming:**
  ML learns rules from data, traditional programming uses predefined rules
- **Features matter:**
  Choose meaningful features, avoid arbitrary identifiers
- **Classification vs Regression:**
  Discrete outputs vs continuous outputs
- **Accuracy isn't everything:**
  For imbalanced data, use precision, recall, F1-score
- **Visualization is crucial:**
  Always plot your data first
- **Use baselines:**
  Simple baseline models help validate your approach

Summary: Evaluation Metrics

Task	Common Metrics	When to Use
Classification	Accuracy, Precision, Recall, F1 Confusion Matrix	Balanced/Imbalanced data Multi-class problems
Regression	MSE, RMSE, MAE Mean Error	Continuous predictions Check for bias

Remember

Choose metrics based on your problem's characteristics and business requirements!